CSCI567 Machine Learning (Fall 2018)

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U of Southern California

Sep 26, 2018

Administration

HW 2 released, due on 10/07

HW 1 solutions are available, W1 is graded, P1 grading should be done by the end of this week

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Midterm

- 10/03, 5PM-7PM, *THH 101 and THH 201* (pick any one), sit every other seat, closed-book/notes, no electronics allowed
- Multiple choice + regular problems like homework
- Coverage: mostly Lec 1-5, some simple questions from Lec 6 (today)

Outline

1. Review of last lecture

2. Support vector machines (primal formulation)

3. A detour of Lagrangian duality

4. Support vector machines (dual formulation)

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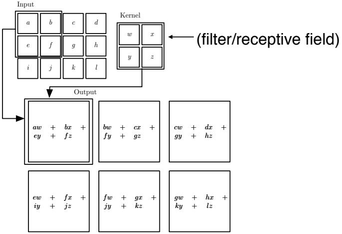
Convolutional Neural Nets

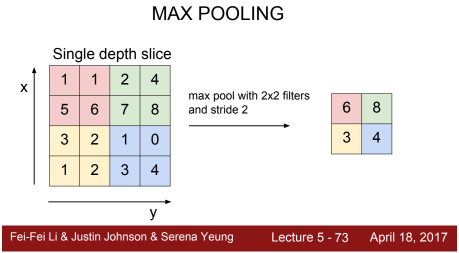
Typical architecture for CNNs:

Input → [[Conv → ReLU]*N → Pool?]*M → [FC → ReLU]*Q → FC

2D Convolution



(Goodfellow 2016)



Kernel functions

Definition: a function $k : \mathbb{R}^{\mathsf{D}} \times \mathbb{R}^{\mathsf{D}} \rightarrow \mathbb{R}$ is called a *(positive semidefinite) kernel function* if there exists a function $\boldsymbol{\phi} : \mathbb{R}^{\mathsf{D}} \rightarrow \mathbb{R}^{\mathsf{M}}$ so that for any $\boldsymbol{x}, \boldsymbol{x}' \in \mathbb{R}^{\mathsf{D}}$,

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Examples we have seen

$$k(\boldsymbol{x}, \boldsymbol{x}') = (\boldsymbol{x}^{\mathrm{T}} \boldsymbol{x}')^2$$

$$k(\boldsymbol{x}, \boldsymbol{x}') = \sum_{d=1}^{\mathsf{D}} \frac{\sin(2\pi(x_d - x'_d))}{x_d - x'_d}$$

$$k(\boldsymbol{x}, \boldsymbol{x}') = (\boldsymbol{x}^{\mathrm{T}} \boldsymbol{x}' + c)^d \qquad \text{(polynomial kernel)}$$

$$k(\boldsymbol{x}, \boldsymbol{x}') = e^{-\frac{\|\boldsymbol{x} - \boldsymbol{x}'\|_2^2}{2\sigma^2}} \qquad \text{(Gaussian/RBF kernel)}$$

Kernelizing ML algorithms

Feasible as long as **only inner products are required**:

- regularized linear regression (dual formulation)

$$\phi(x)^{\mathrm{T}} w^* = \phi(x)^{\mathrm{T}} \Phi^{\mathrm{T}} (K + \lambda I)^{-1} y \quad (K = \Phi\Phi^{\mathrm{T}} \text{ is } \textit{kernel matrix})$$

- nearest neighbor classifier with L2 distance

$$\|\phi(x) - \phi(x')\|_2^2 = k(x, x) + k(x', x') - 2k(x, x')$$

- perceptron, logistic regression, SVM, ...

Outline

Support vector machines (SVM)

- One of the most commonly used classification algorithms
- Works well with the kernel trick
- Strong theoretical guarantees

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We focus on **binary classification** here.

Primal formulation

In one sentence: linear model with L2 regularized hinge loss.

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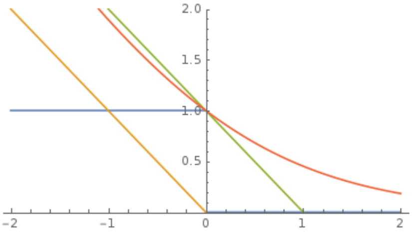

- perceptron loss $\ell_{\text{perceptron}}(z) = \max\{0, -z\} \rightarrow$ Perceptron
- logistic loss $\ell_{\text{logistic}}(z) = \log(1 + \exp(-z)) \rightarrow$ logistic regression
- hinge loss $\ell_{\text{hinge}}(z) = \max\{0, 1 - z\} \rightarrow$ **SVM**

Primal formulation

For a linear model $(\boldsymbol{w}, b)$, this means

$$\min_{\boldsymbol{w},b} \sum_n \max\left\{0, 1 - y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b)\right\} + \frac{\lambda}{2}\|\boldsymbol{w}\|_2^2$$

- recall $y_n \in \{-1, +1\}$
- a nonlinear mapping $\boldsymbol{\phi}$ is applied
- the bias/intercept term b is used explicitly (think about why after this lecture)

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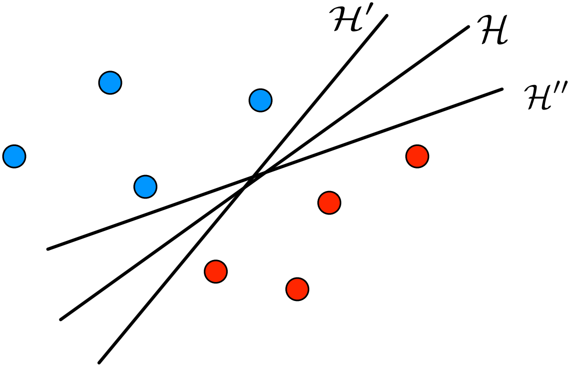
So why L2 regularized hinge loss?

Geometric motivation: separable case

When data is **linearly separable**, there are *infinitely many hyperplanes with zero training error*:



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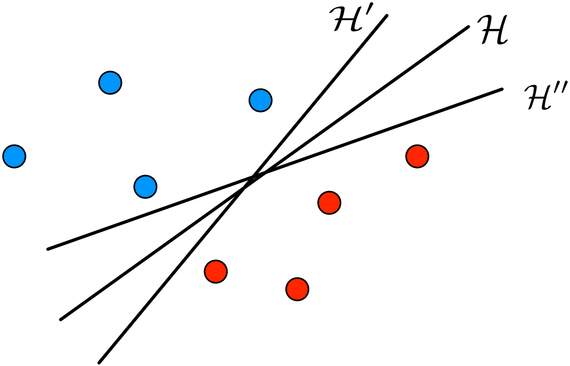
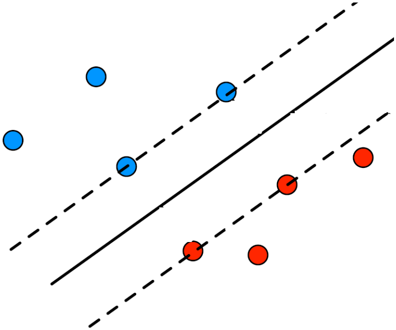


So which one should we choose?

Intuition

The further away from data points the better.



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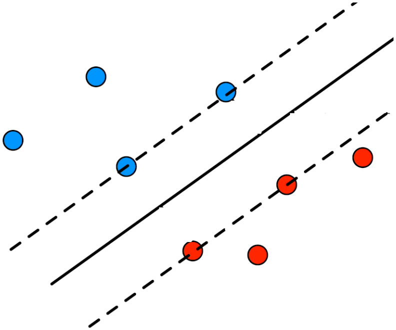

How to formalize this intuition?

Distance to hyperplane

What is the **distance** from a point $\boldsymbol{x}$ to a hyperplane $\{\boldsymbol{x} : \boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b = 0\}$?

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$$0 = \boldsymbol{w}^{\mathrm{T}}\left(\boldsymbol{x} - \ell\frac{\boldsymbol{w}}{\|\boldsymbol{w}\|_2}\right) + b = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} - \ell\|\boldsymbol{w}\| + b$$

and thus $\ell = \frac{\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}+b}{\|\boldsymbol{w}\|_2}$.

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Therefore the distance is

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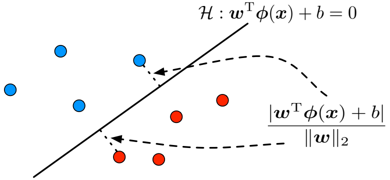
For a hyperplane that correctly classifies $(\boldsymbol{x}, y)$, the distance becomes

$$\frac{y(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b)}{\|\boldsymbol{w}\|_2}$$

Maximizing margin

Margin: the *smallest* distance from all training points to the hyperplane

$$\text{MARGIN OF } (\boldsymbol{w}, b) = \min_n \frac{y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b)}{\|\boldsymbol{w}\|_2}$$



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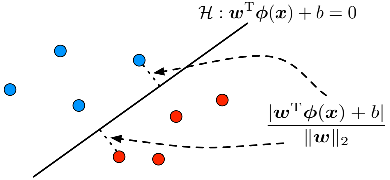

The intuition "**the further away the better**" translates to solving

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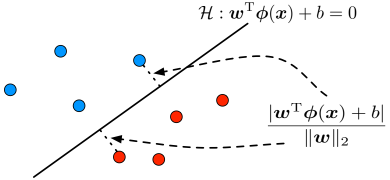

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$$\max_{\boldsymbol{w},b} \quad \min_n \frac{y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b)}{\|\boldsymbol{w}\|} = \max_{\boldsymbol{w},b} \frac{1}{\|\boldsymbol{w}\|_2} \min_n y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b)$$

Rescaling

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We can thus always scale $(\boldsymbol{w}, b)$ s.t. $\min_n y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b) = 1$

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The margin then becomes

$$
\begin{aligned}
&\textsc{margin of } (\boldsymbol{w},\, b) \\
&= \frac{1}{\|\boldsymbol{w}\|_2} \min_n y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b) \\
&= \frac{1}{\|\boldsymbol{w}\|_2}
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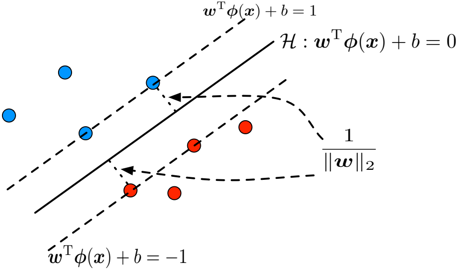

Summary for separable data

For a separable training set, we aim to solve

$$\max_{\boldsymbol{w},b} \frac{1}{\|\boldsymbol{w}\|_2} \quad \text{s.t.} \quad \min_n y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b) = 1$$

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SVM is thus also called *max-margin* classifier. The constraints above are called *hard-margin* constraints.

General non-separable case

If data is not linearly separable, the previous constraint

$$y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b) \geq 1, \quad \forall\ n$$

is obviously *not feasible*.

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To deal with this issue, we relax them to **soft-margin** constraints:

$$y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b) \geq 1 - \xi_n, \quad \forall\ n$$

where we introduce **slack variables** $\xi_n \geq 0$.

SVM Primal formulation

We want ξ_n to be as small as possible too.

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We want ξ_n to be as small as possible too. The objective becomes

$$\begin{aligned} \min_{\boldsymbol{w}, b, \{\xi_n\}} \quad & \frac{1}{2}\|\boldsymbol{w}\|_2^2 + C \sum_n \xi_n \\ \text{s.t.} \quad & y_n(\boldsymbol{w}^{\mathrm{T}} \boldsymbol{\phi}(\boldsymbol{x}_n) + b) \geq 1 - \xi_n, \quad \forall\, n \\ & \xi_n \geq 0, \quad \forall\, n \end{aligned}$$

where C is a hyperparameter to balance the two goals.

Equivalent form

Formulation

$$
\begin{aligned}
\min_{\boldsymbol{w}, b, \{\xi_n\}} \quad & C \sum_n \xi_n + \frac{1}{2}\|\boldsymbol{w}\|_2^2 \\
\text{s.t.} \quad & 1 - y_n(\boldsymbol{w}^{\mathrm{T}} \boldsymbol{\phi}(\boldsymbol{x}_n) + b) \leq \xi_n, \quad \forall\ n \\
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with $\lambda = 1/C$.

Equivalent form

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with $\lambda = 1/C$. *This is exactly minimizing L2 regularized hinge loss!*

Optimization

$$\begin{aligned} \min_{\boldsymbol{w}, b, \{\xi_n\}} \quad & C \sum_n \xi_n + \frac{1}{2}\|\boldsymbol{w}\|_2^2 \\ \text{s.t.} \quad & 1 - y_n(\boldsymbol{w}^{\mathrm{T}} \boldsymbol{\phi}(\boldsymbol{x}_n) + b) \leq \xi_n, \quad \forall\ n \\ & \xi_n \geq 0, \quad \forall\ n \end{aligned}$$

- It is a convex (**quadratic** in fact) problem

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- It is a convex (**quadratic** in fact) problem
- thus can apply any convex optimization algorithms, e.g. SGD
- there are **more specialized and efficient** algorithms
- but usually we apply kernel trick, which requires solving the *dual problem*

Outline

Lagrangian duality

Extremely important and powerful tool in analyzing optimizations

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We will introduce basic concepts and derive the **KKT conditions**

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Applying it to SVM reveals an important aspect of the algorithm

Primal problem

Suppose we want to solve

$$\min_{\boldsymbol{w}} F(\boldsymbol{w}) \quad \text{s.t. } h_j(\boldsymbol{w}) \leq 0 \quad \forall\, j \in [\mathsf{J}]$$

where functions $h_1, \ldots, h_{\mathsf{J}}$ define J **constraints**.

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SVM primal formulation is clearly of this form with $\mathsf{J} = 2\mathsf{N}$ constraints:

$$F(\boldsymbol{w}, b, \{\xi_n\}) = C\sum_n \xi_n + \frac{1}{2}\|\boldsymbol{w}\|_2^2$$

$$h_n(\boldsymbol{w}, b, \{\xi_n\}) = 1 - y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b) - \xi_n \quad \forall\, n \in [\mathsf{N}]$$

$$h_{\mathsf{N}+n}(\boldsymbol{w}, b, \{\xi_n\}) = -\xi_n \quad \forall\, n \in [\mathsf{N}]$$

Lagrangian

The **Lagrangian** of the previous problem is defined as:

$$L(\boldsymbol{w}, \{\lambda_j\}) = F(\boldsymbol{w}) + \sum_{j=1}^{\mathsf{J}} \lambda_j h_j(\boldsymbol{w})$$

where $\lambda_1, \ldots, \lambda_{\mathsf{J}} \geq 0$ are called **Lagrangian multipliers**.

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Note that

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and thus,

$$\min_{\boldsymbol{w}} \max_{\{\lambda_j\}\geq 0} L\left(\boldsymbol{w}, \{\lambda_j\}\right) \iff \min_{\boldsymbol{w}} F(\boldsymbol{w}) \ \text{ s.t. } \ h_j(\boldsymbol{w}) \leq 0 \quad \forall\, j \in [\mathsf{J}]$$

Duality

We define the **dual problem** by swapping the min and max:

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How are the primal and dual connected?

Duality

We define the **dual problem** by swapping the min and max:

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This is called "**weak duality**".

Strong duality

When $F, h_1, \ldots, h_m$ are convex, under some mild conditions:

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Deriving the Karush-Kuhn-Tucker (KKT) conditions

Observe that if strong duality holds:

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- equality $\min_{\boldsymbol{w}} L(\boldsymbol{w}, \{\lambda_j^*\}) = L(\boldsymbol{w}^*, \{\lambda_j^*\})$ implies $\boldsymbol{w}^*$ is a **minimizer** of $L(\boldsymbol{w}, \{\lambda_j^*\})$ and thus has **zero gradient**:

$$\nabla_{\boldsymbol{w}} L(\boldsymbol{w}^*, \{\lambda_j^*\}) = \nabla F(\boldsymbol{w}^*) + \sum_{j=1}^{\mathsf{J}} \lambda_j^* \nabla h_j(\boldsymbol{w}^*) = \boldsymbol{0}$$

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These are *necessary conditions*.

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These are *necessary conditions*. They are also *sufficient* when F is convex and $h_1, \ldots, h_{\mathsf{J}}$ are continuously differentiable convex functions.

Outline

Writing down the Lagrangian

Recall the primal formulation

$$\begin{aligned}\min_{\boldsymbol{w},b,\{\xi_n\}} \quad & C\sum_n \xi_n + \frac{1}{2}\|\boldsymbol{w}\|_2^2 \\ \text{s.t.} \quad & 1 - y_n[\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b] \leq \xi_n, \quad \forall\ n \\ & \xi_n \geq 0, \quad \forall\ n\end{aligned}$$

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Lagrangian is

$$\begin{aligned} L\left(\boldsymbol{w}, b, \{\xi_n\}, \{\alpha_n\}, \{\lambda_n\}\right) = {} & C \sum_n \xi_n + \frac{1}{2}\|\boldsymbol{w}\|_2^2 - \sum_n \lambda_n \xi_n \\ & + \sum_n \alpha_n \left(1 - y_n(\boldsymbol{w}^{\mathrm{T}} \boldsymbol{\phi}(\boldsymbol{x}_n) + b) - \xi_n\right) \end{aligned}$$

where $\alpha_1, \ldots, \alpha_{\mathsf{N}} \geq 0$ and $\lambda_1, \ldots, \lambda_{\mathsf{N}} \geq 0$ are Lagrangian multipliers.

Applying the stationarity condition

$$L = C\sum_n \xi_n + \frac{1}{2}\|\boldsymbol{w}\|_2^2 - \sum_n \lambda_n \xi_n + \sum_n \alpha_n \left(1 - y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b) - \xi_n\right)$$

$\exists$ primal and dual variables $\boldsymbol{w}, b, \{\xi_n\}, \{\alpha_n\}, \{\lambda_n\}$ s.t. $\nabla_{\boldsymbol{w},b,\{\xi_n\}} L = \mathbf{0}$,

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Rewrite the Lagrangian in terms of dual variables

Replacing $\boldsymbol{w}$ by $\sum_n y_n \alpha_n \boldsymbol{\phi}(\boldsymbol{x}_n)$ in the Lagrangian gives

$$L = C\sum_n \xi_n + \frac{1}{2}\|\boldsymbol{w}\|_2^2 - \sum_n \lambda_n \xi_n + \sum_n \alpha_n \left(1 - y_n(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x}_n) + b) - \xi_n\right)$$

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($\sum_n \alpha_n y_n = 0$ and $C = \lambda_n + \alpha_n$)

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The dual formulation

To find the dual solutions, it amounts to solving

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\text{s.t.} \quad & \sum_n \alpha_n y_n = 0 \\
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$$C - \lambda_n - \alpha_n = 0, \; \alpha_n \geq 0, \; \lambda_n \geq 0, \quad \forall\, n$$

Note the last three constraints can be written as $0 \leq \alpha_n \leq C$ for all n.

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Note the last three constraints can be written as $0 \leq \alpha_n \leq C$ for all n. So the final **dual formulation of SVM** is:

$$\begin{aligned} \max_{\{\alpha_n\}} \quad & \sum_n \alpha_n - \frac{1}{2}\sum_{m,n} y_m y_n \alpha_m \alpha_n \boldsymbol{\phi}(\boldsymbol{x}_m)^{\mathrm{T}} \boldsymbol{\phi}(\boldsymbol{x}_n) \\ \text{s.t.} \quad & \sum_n \alpha_n y_n = 0 \quad \text{and} \quad 0 \leq \alpha_n \leq C, \quad \forall\ n \end{aligned}$$

Kernelizing SVM

Now it is clear that with a **kernel function** k for the mapping ϕ, we can kernelize SVM as:

$$\max_{\{\alpha_n\}} \quad \sum_n \alpha_n - \frac{1}{2}\sum_{m,n} y_m y_n \alpha_m \alpha_n k(\boldsymbol{x}_m, \boldsymbol{x}_n)$$

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Again, no need to compute $\phi(\boldsymbol{x})$.

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$$\text{s.t.} \quad \sum_n \alpha_n y_n = 0 \quad \text{and} \quad 0 \le \alpha_n \le C, \quad \forall\ n$$

Again, no need to compute $\phi(\boldsymbol{x})$. It is a **quadratic program** and many efficient optimization algorithms exist.

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To identify b, we need to apply complementary slackness.

Applying complementary slackness

For all n we should have

$$\lambda_n^* \xi_n^* = 0, \quad \alpha_n^* \left(1 - \xi_n^* - y_n(\boldsymbol{w}^{*\mathrm{T}} \boldsymbol{\phi}(\boldsymbol{x}_n) + b^*)\right) = 0$$

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The prediction on a new point $\boldsymbol{x}$ is therefore

$$\mathrm{SGN}\left(\boldsymbol{w}^{*\mathrm{T}} \boldsymbol{\phi}(\boldsymbol{x}) + b^*\right) = \mathrm{SGN}\left(\sum_m y_m \alpha_m^* k(\boldsymbol{x}_m, \boldsymbol{x}) + b^*\right)$$

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A support vector satisfies $\alpha_n^* \neq 0$ and

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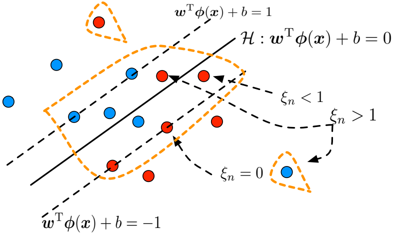

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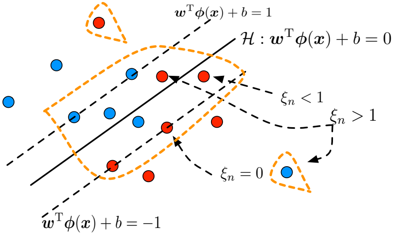

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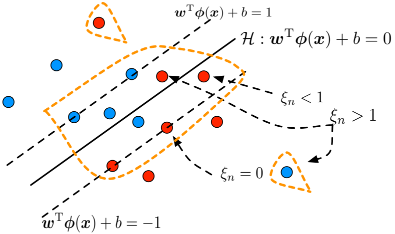

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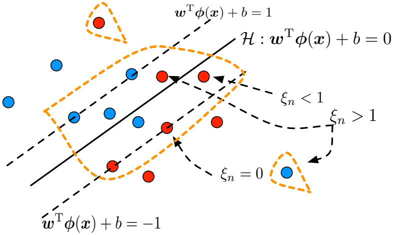

Support vectors (circled with the orange line) are *the only points that matter!*

An example

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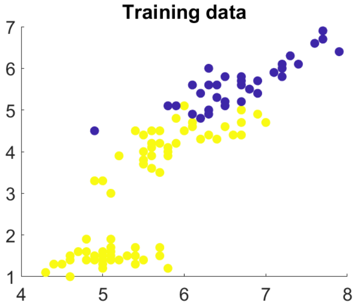

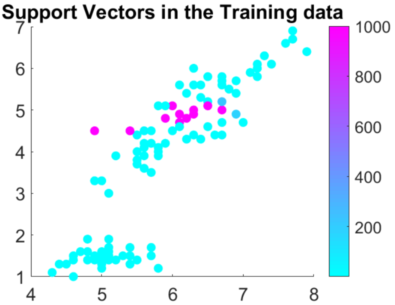

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Primal (equivalent to minimizing L2 regularized hinge loss):

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Dual (kernelizable, reveals what training points are support vectors):

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